A

Research Proposal

on

“Analysis of EEG Signals by Machine Learning and Deep Learning Algorithms”

by

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(2021PEC201)

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Abstract

Analysis of EEG data is difficult due to their complexity and noise. Manual feature extraction and categorization are frequently used in traditional approaches to EEG signal analysis. However, these techniques can be laborious and prone to mistakes.

Recent research has demonstrated the efficacy of deep learning approaches for analysing EEG signals. Deep learning algorithms can automatically extract features from unprocessed EEG signals, enhancing the precision of other tasks like categorization.

For the analysis of EEG signals, a variety of deep learning architectures can be applied. 'Convolutional Neural Networks' (CNNs), 'Recurrent Neural Networks' (RNNs), and 'Deep Belief Networks' (DBNs) are a few of the most well-liked architectures. Several EEG signal processing tasks have been tackled using deep learning approaches, such as: classification of many brain states, including awakeness, sleep, and various seizure forms, detection of cognitive activities like memory, motor imagery, and attention, diagnosis of neurological conditions such epilepsy, Alzheimer's disease and Parkinson's disease.

In this study, we concentrate on the classification of EEG data utilising cutting-edge deep learning and machine learning methods.

Our study makes use of a varied EEG dataset that includes recordings made during various cognitive and neurological states. The main goal of our investigation is to remove noise, artefacts, and extraneous information from EEG data, we carefully preprocess it. This process guarantees the accuracy and dependability of the data used for the analysis. To convert unprocessed EEG signals into useful information, we use sophisticated feature extraction techniques. These features identify crucial EEG data patterns that are symptomatic of different neurological or cognitive problems.

'Convolutional Neural Networks' and 'Recurrent Neural Networks' are two examples of deep learning models that are used to automatically learn hierarchical representations from EEG data. To categorise EEG signals into different groups, such as stages of sleep, cognitive states, or neurological illnesses, these models are trained.

We would like to investigate advanced machine learning methods, such as 'Support Vector Machines' (SVMs), 'Decision Trees' and 'Random Forests' in addition to deep learning. This makes it possible to compare the efficiency and performance of deep learning with traditional techniques. We examine the adaptability of our models to various EEG datasets, domains, and tasks. This aids in our comprehension of the flexibility and reliability of our classification techniques.

Our research places a strong emphasis on how easily classification results can be understood. To better understand neural processes, we use visualisation methods and saliency maps to uncover the features that matter most in classification judgements.

1. Introduction

The non-invasive neuroimaging technique known as electroencephalography, or EEG, is crucial for both therapeutic treatment and the study of neuroscience. With the aid of this technology, the electrical activity the brain generates is largely detected and captured. Electrodes placed on the scalp are used to capture this electrical activity, and the resulting signals, known as EEG signals, provide crucial information on the activity and function of the brain.

The high temporal resolution of EEG data allows scientists and medical experts to detect the millisecond fluctuations of the brain in real time. These signals are voltage fluctuations produced by the coordinated firing of several millions of neurons. EEG is particularly useful for examining several aspects of brain function, including:

1. Brain Waves: EEG signals are frequently divided into multiple frequency bands, each of which is linked to distinct cognitive states. These frequencies fall into the ranges of ‘Delta (0.5–4 Hz)’, ‘Theta (4–8 Hz)’, ‘Alpha (8–13 Hz)’, ‘Beta (13–30 Hz)’ and ‘Gamma (>30 Hz)’. These waves are connected to a variety of mental states, including vigilance, relaxation, and deep sleep.
2. ERPs: Electroencephalography (EEG) is commonly used to research ERPs, which are specific brain reactions triggered by sensory, motor, or cognitive inputs. ERPs provide information about a variety of cognitive functions, including attention, memory, and decision-making.
3. Seizure Detection: Epilepsy and other seizure disorders can be diagnosed and monitored with the help of the EEG. It can help choose the best course of action by detecting aberrant electrical patterns linked to seizures.
4. Sleep Research: EEG is crucial in sleep studies because it allows for the classification of sleep stages, the detection of sleep disorders, and the assessment of sleep quality.
5. Neurofeedback: To help people control their brain activity, neurofeedback training that is based on EEG is used. ADHD, anxiety, and post-traumatic stress disorder are among the disorders it can be used to treat.

6. Brain-Computer Interfaces (BCIs): BCIs, which enable people to directly operate computers or prosthetic equipment with their thoughts, are created using EEG signals. For persons with disabilities, this technology holds transformative promise.

By attaching electrodes to the scalp, an EEG device monitors and documents brain wave patterns. Two electrode placement systems are used:

a) the 10-20 international system, which uses 21 electrodes

b) The 64 electrodes of the 10-10 international system [1].

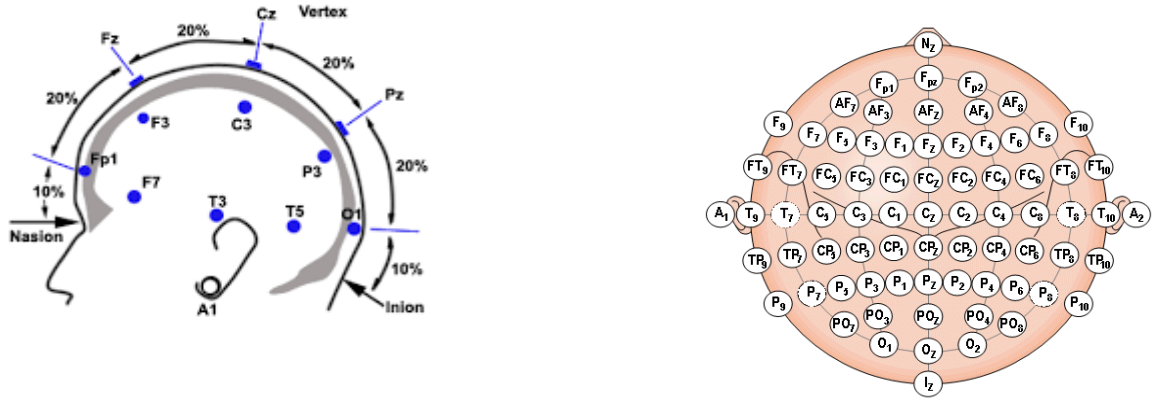

Fig 1.a) 10-20 International System b) 10-10 International System

As opposed to intracranial EEG, which involves surgically implanting electrodes over the brain surface, conventional EEG uses electrodes to detect brain electrical activity from outside the skull.

Hemispheres refer to one of the two sides of the brain. A lobe system divides each hemisphere:

1. Frontal Lobe: Executive functions oversee more complex cognitive processes like planning, judgement, problem-solving, and reasoning. Controls coordination and voluntary muscular movements in the motor cortex. Emotional regulation and personality characteristics are influenced by each other.
2. Parietal Lobe: Our ability to feel touch, pressure, warmth, and pain is due to the somatosensory cortex, which processes sensory data from the skin, muscles, and joints. Plays a significant part in spatial orientation and perception. A coherent perception of the environment is produced through the integration of sensory information, which combines sensory inputs.
3. Temporal Lobe: Sound perception and speech understanding are among the auditory information that must be processed. Long-term memory formation is the process by which long-term memories are created and retrieved.

4. Occipital Lobe: Processing of visual information acquired from the eyes that enables humans to recognise and make sense of visual stimuli, such as motion, colour, and shape.The primary visual cortex is where visual information is processed.

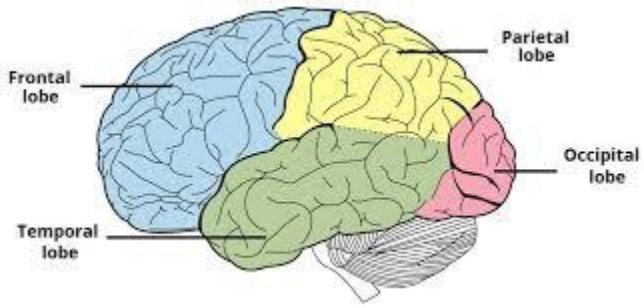

Fig 2. Brain Lobes

A microvolt-range EEG signal has frequency bands that span from 0.1 Hz to 40.0 Hz, and studies of higher frequencies than 30 Hz are challenging because the different regions of the skull and scalp dampen these frequencies. Like before, muscle artefacts block out higher frequencies. Application-specific criteria must always be considered when selecting a sub-band to analyse within the usable frequency range [2]. The following are different interest sub-bands:

- Delta (0.5–4 Hz): The slowest waves, delta waves are connected to deep slumber.
- Theta (4–8 Hz): Theta waves are related to REM sleep, daydreaming, and calm wakefulness.
- Alpha (8–12 Hz): Alpha waves are related to alertness that is calm and concentration that is focused.
- Beta (13–30 Hz): Active attention, focus, and problem-solving are all correlated with beta waves.
- Gamma (30-100 Hz): Gamma waves are related to memory, consciousness, and learning.

The Greek alphabets are used to denote the frequency bands, which are commonly measured in hertz (Hz). The number of times an EEG wave completes a cycle in a second is its frequency.

Different brain activities are linked to various frequency ranges. For instance, alpha waves are linked to concentrated attention, beta waves to active attention, and gamma waves to learning, memory, and consciousness. Delta waves are linked to profound sleep, theta waves to relaxed wakefulness, and beta waves to active attention.

Different brain states and cognitive abilities can be evaluated using the relative power of the various frequency bands. For instance, an increase in delta waves could signify deep sleep, an increase in theta waves could signify relaxed wakefulness, an increase in alpha waves could signify focused attention, an increase in beta waves could signify active attention, and an increase in gamma waves could signify learning and consciousness.

The EEG frequency bands can be used to analyse the electrical activity of the brain, evaluate various mental states, and measure cognitive abilities.

2. Literature Review

To assess the electrical activity of the brain, EEG mostly uses electrodes placed on the scalp. The signal waves that were captured include important data about the condition of the brain. When small excitatory postsynaptic potentials are generated by pyramidal neurons in the cortical layers of the brain, EEG really captures the electric potential changes of tens of microvolts (V) reaching the scalp [3].

Nevertheless, the signals can still be softened by utilising a 'Principal Component Analysis' (PCA) and 'Fast Fourier Transform' (FFT) to identify the characteristics to input a RF (Random Forest) model. In [8], the time-frequency analysis is used to characterise those properties that define the signal it sees, frequencies that changes slowly over time are those called as non-stationary signals. Clean and pre-processing of the EEG signals are important aspects.

An EEG dataset's representation of the scalp-based brain potentials is a 2D in channel and time real-valued matrix. These potentials are connected to certain completed tasks or situations. Machine learning (ML) algorithms have drawn significant study effort in recent studies, according to several successful investigations [4][5][6]. In fact, ML techniques are particularly well suited for studying EEG data. It is true that ML can handle big and complicated data sets while emphasising the identification of intricate patterns and the production of precise predictions and classifications. The 'Support Vector Machine' (SVM), 'Maximum Entropy', 'Long Short-Term Memory' and 'Convolutional Neural Network' (CNN) methods of Machine Learning (ML) are used to analyse emotions. Several studies have been conducted to find new findings regarding age and gender for sentiment analytics.

Deep Learning (DL) has changed the way that machine learning is thought about during the past ten years. It has made particularly notable strides in a number of application sectors like ‘Computer Vision’, ‘Automatic Speech Recognition’, ‘Natural Language Processing’ and ‘Bioinformatics’, where they deliver cutting-edge outcomes on a variety of tasks. DL has enormous potential for improving the interpretation of EEG information. To create features from the raw data, the DL does not need specialised subject knowledge. Although there have been more empirical investigations dealing with the application of DL in EEG analysis, a summary of the published research is missing from the literature. In fact, only few articles [7] have examined the subject from a literary standpoint. As a result, little is known about several crucial factors, such as trends, problems, difficulties, and future study directions. In each case, we conducted a thorough literature evaluation of the use of DL for EEG data interpretation. Overall, DL extends and improves on current EEG processing techniques in a number of different ways. First, because DNNs are hierarchical, it is unnecessary to use feature extraction and processing pipelines that are specifically designed for each domain because features may be learned on raw or hardly pre-processed data. Additionally, characteristics learnt by a DNN could be more beneficial or expressive than those created by humans.

Second, much like in the many sectors where Deep Learning has exceeded the preceding state-of-the-art, it has the potential to produce greater levels of performance on many analysis tasks. Third, leveraging EEG data to generate activities like generative modelling [9] and domain adaptation [10] that are less commonly done is made simpler by DL. The use of deep learning-based approaches allowed for the synthesis of the data. To improve data or represent intermediate representation can be created by generative models [9].

Correlation alignment technique in deep neural networks [11] where domain-invariant representations enabled by end-to-end learning while keeping task-dependent information when it comes to domain adaption. Similar methods can be applied to EEG data to improve model performance and create better representations for a range of topics and tasks.

There are a number of reasons that DL might not prove to be the best method for interpreting EEG data, which may help to explain the EEG community's resistance. Primarily, when compared to datasets used to develop the latest techniques in DL-intensive fields like "Computer Vision" (CV) and "Natural Language Processing" (NLP), the datasets usually utilised in EEG research have significantly less samples. Openly accessible datasets of comparable proportions are uncommon since data collection is often expensive and data

accessibility is frequently hampered by privacy concerns—especially with clinical data. However, several programmes have tried to address this issue [12]. Second, due to the peculiarities of EEG, low in signal to noise ratio, electroencephalogram data is different from other categories of data (such as pictures, voice and text) for which DL has been utilised.

Auto-encoder [13] from deep learning approaches vary in literature, cnn [14], rnn [15], lstm [16] and to a most advanced techniques like syncnet [17], EEGNet [18], EEGChannelNet [19] and GCN [18]. RNN and LSTM are used for analysing long sequences of high temporal EEG signals. They train the data one by one at each time step, thus lengthening the training period for convergence. Additionally, although some deep learning frameworks, long-term dependencies such as RNN-based models and neighbouring interactions can capture temporal dependencies with CNN-based models, they can only perform to a limited extent when the sequences are exceedingly long (see, for example, [20]).

3.Methodology

1.Data collection: The initial step is to obtain the subjects' EEG data. There are many ways to accomplish this, including wearing a cap with electrodes fastened to the scalp or a headset with electrodes built into the ear cups.

2.Data preprocessing: Preprocessing data is the following step after collecting the EEG data. This entails filtering out background noise from the data, such as muscle and ocular electrical activity. Additionally, the data must be normalised for it to be in a standard format.

- Artifact rejection: Rejection of artefacts: Artefacts are undesired signals that can taint EEG data. Eye blinks, skeletal movements, and power line noise are typical artefacts. These artefacts can be eliminated from the data using artefact rejection techniques.
- Bandpass filtering: EEG signals are frequently subjected to bandpass filtering to reduce noise and concentrate on key frequency ranges. For instance, the beta band (13–30 Hz) is frequently used to investigate cognition, whereas the alpha band (8–12 Hz) is frequently used to study attention.
- Baseline correction: The DC component of the EEG data is eliminated using this procedure. The signal's average value, or DC component, can be occurred by various things, containing muscle activity and electrode impedance.

- Normalization: It is a method for ensuring that EEG data is comparable between people and sessions. To do this, the data are scaled to have a mean and standard deviation of 0 and 1, respectively.

The EEG signal analysis task at hand as well as the attributes of the data will determine the preprocessing procedures that are performed. The following are some advantages of preprocessing EEG signals:

- The accuracy of EEG signal analysis may be enhanced.
- It may make it simpler to locate the pertinent signals by lowering the data's noise levels.
- The data may become more comparable between topics and sessions as a result.
- The data may be better suited for machine learning algorithms as a result.

3.Feature extraction: The third phase involves extracting features from the EEG data. The qualities of the data that are pertinent to the classification process are referred to as features. The power in various frequency bands, the correlation between various channels, and the time-frequency distribution of the data are only a few of the numerous aspects that may be derived from EEG data.

4.Model selection: The fourth stage entails choosing a deep learning model. ‘Deep Belief Networks’ (DBNs), ‘Recurrent Neural Networks’ (RNNs) and ‘Convolutional Neural Networks’ (CNNs) are just a few of the various deep learning models that can be used to classify EEG signals. The specific categorization task and the EEG data's features will determine which model is used.

5.Model training: The deep learning model must be trained in this stage. This entails providing the model with the EEG data and modifying the model's parameters to enable proper data classification.

6.Model Evaluation: Evaluating how well the deep learning model performs can be seen in this phase. A held-out dataset or a cross-validation method can be used to test the model in this situation.

4.Proposed Research Work

RO1: To decompose EEG signals and to analyse the cognitive load index, band ratio’s, prefrontal electrode, individual band frequencies of the subjects and binary classification with different classifier.

RO2: To analyse and implement a different classifier using machine learning techniques for classification of brain lobe areas and pair-wise electrode combination.

RO3: To propose a novel technique using transformer-based model for classification.

RO4: To propose a novel technique using convolution layers, resnet layer along with transformer for classification.

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